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Promoting the Quality of Cross-Domain Knowledge Item Obtainment in University Digital Libraries by Utilizing the Graphormer-Lite Graph Coding Model

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SUMMARY: *Addressing the challenges of coexisting objects such as books, journal articles, theses, and course resources in university digital libraries, as well as weak cross-database associations and insufficient hierarchical organization, this paper proposes a cross-domain knowledge item association retrieval method based on the Graphormer-Lite graph encoding model. This research firstly builds a heterogeneous graph that includes books, journal papers, dissertations, course materials, subject words, writers, universities/branches of learning, and database origins, thus it unifies textual content, catalog properties, structure connections, and user actions in one single expression space. Based upon this foundation, the research puts forward relationship type bias, path distance coding, and local candidate attention, therefore it reduces the inference extra cost via layer compression, parameter sharing, and distillation methods. Experiments were conducted using 6 subject domains, 120,000 core knowledge entry nodes, approximately 2.15 million relationship edges, and 38,624 click and download logs. Results show that Graphormer-Lite achieves 0.684, 0.781, 0.643, and 0.612 on Recall@10,Recall@20, nDCG@10, and MRR of 0.684, 0.781, 0.643, and 0.612, respectively, outperforming BM25, Sentence-BERT, HAN, HGT, and the standard Graphormer overall; it also maintains a stable advantage in long-tail and cold-start scenarios while achieving a balance between latency and parameter size that is more suitable for online deployment. This method provides a reference for optimizing cross-domain resource discovery and association services in university digital libraries.*

KEY WORDS: *Digital library; Cross-domain linked search; Heterogeneous graph; Graphormer-Lite; Knowledge item ranking*

1 Introduction

The information arrangement of university digital libraries is experiencing a change from "collection record searching" to "knowledge connecting services." Along with objects for example books, journal articles, theses, course resources, subject-specific database entries, faculty research outputs, and disciplinary keywords continuously gather together onto a unified service platform, user expectations for retrieval systems no longer stay at the level of individual record hits. On the contrary, users more and more pay attention to whether topic-related resources can be found in a continuous way, with cross-database combination, and with reasonable arranging order. Traditional retrieval frameworks frequently put emphasis on computing similarity between text domains such as titles, abstracts and keywords in processing such tasks, while they do not fully utilize relation paths, object type distinctions, and context

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connections among entries. Existing research already shows that putting heterogeneous graph attention mechanisms into passage retrieval lets retrieval models more effectively use clear connections between objects, therefore solving the information splitting problem which is brought by separated text matching [1].

Correlative progresses in the domain of academic search further make clear that documents, writers, organizations, periodicals, subjects, and study orientations naturally constitute a different-type knowledge net, and search quality is tightly connected with the degree to which this structure information is made use of. Research on academic expert discovery tasks has found that when the retrieval process simultaneously models node types, connection density, and embedding representations, the resulting rankings better reflect the true relationships among academic entities [2]. In the context of scientific paper recommendation, the time-decay heterogeneous graph method mitigates the interference of high connectivity in older literature on ranking results by incorporating factors of knowledge evolution, thereby aligning recommendations more closely with current research hotspots and thematic trends [3]. Another study on literature retrieval constructs a heterogeneous hypergraph based on citation intent, incorporating higher-order relationships such as "support, extension, and contrast" into the modeling framework. This demonstrates that retrieval quality is not only influenced by textual content but is also significantly constrained by fine-grained differences in relational semantics [4]. In the realm of personalized academic search, knowledge graph-enhanced models have demonstrated strong capabilities in topic modeling and interest expression, providing a more refined basis for association-based ranking to address complex search needs [5].

These results have direct connection to the relevant obtaining of cross-domain knowledge pieces in university digital libraries. Compared to general academic search, resource objects in university digital libraries are more complex, encompassing not only highly standardized theses and books but also knowledge items with inconsistent structures, such as course materials, collection topic pages, teaching cases, institution-specific resources, and degree theses. User search behavior also exhibits distinct task-oriented characteristics, such as simultaneously searching for textbooks, review articles, classic case studies, and theses related to a specific course topic. Newer study on meaning getting back in digital libraries has already started to combine graph neural networks, ontology-based meaning, and user behavior hints into one combined frame to raise the quality of resource finding and knowledge direction, thus showing that graph structure building now has a practical base for use in digital library situation [6]. Furthermore, research on interpretable answer retrieval based on heterogeneous network embeddings indicates that when models can explicitly express structural paths between resources, the system is better able to generate understandable ranking criteria. This is particularly critical for university digital libraries, as cross-domain item association retrieval must not only return relevant results but also enable users to understand why these items are presented together [7].

From the angle of the development of knowledge arrangement and services, the promotion of cross-domain search abilities cannot be separated from the support of high-quality knowledge graphs. CS-KG 2.0 shows the methods of constructing and reusing large-scale knowledge graphs in computer science domain, thus it gives a comparatively ripe schema design method for the united expression of multi-source academic objects [8]. PubMed Knowledge Graph 2.0, on the other hand, has put together papers, patents, and clinical tests into one single knowledge net work, hence it shows that structured connections among objects from different sources can greatly enlarge the boundary of evidence and the depth of association that retrieval systems possess [9]. For university digital libraries, this graph-shaped organizing method provides big inspiration: if books, courses, theses, topic knowledge pages, and research achievements can all be uniformly turned into calculable nodes, and if the connections between them—like citation relations, co-appearance, subject belonging, teaching links, and use rules—can be further depicted, then cross-domain article searching will get the chance to change from "parallel results from many channels" to "ordered arrangement according to connection intensity."

Recently conducted investigations in the domain of educational knowledge services continuously push forward this tendency. Research on educational knowledge graph-based question answering for the discipline of automatic control indicates that stable semantic mappings can be built between course knowledge, specialized concepts, and user questions, therefore enhancing the precision of educational resource searching and knowledge-based question answering [10]. After that, the put-forward multimodal disciplinary knowledge graph strengthening models further combine text, pictures and disciplinary structure information into one search chain, hence showing the application possibility of cross-modal connection arrangement for education resources [11]. Based on this, an educational question answering frame which combines knowledge graphs with agent retrieval augmentation generation has pushed knowledge graphs from a background arrangement tool to an active inference supporting layer, which shows a tendency for the development of educational knowledge service systems from static searching to dynamic connection and deep response [12]. Putting together, these research works show that the core ability of future digital libraries is moving from competition regarding the size of resource gathering to competition regarding the quality of knowledge linkages; The people who can with higher effectiveness depict the structural connections among resources have more possibility to promote the retrieval quality in the situation of complex work tasks.

However, there still exists an obvious gap between the current research work and the actual demands of university digital libraries. On one hand, majority of existing methods put emphasis on literature recommendation, question answering, or expert searching, and till now there still has not been unified association modeling built for complex object systems like "books—articles—dissertations—course resources—subject words—writers." On another hand, although traditional graph neural networks are able to use adjacency relations for information transmission, their capability in representing multi-hop paths, global structures and complex relation combinations has restriction. Although entire-graph Transformers have more powerful structure modeling abilities, they are frequently followed by problems such as a great quantity of parameters, high inference expenses, and high deployment expenses, therefore making it hard to directly suit the dual restrictions of service response time and calculation cost in university digital libraries. Furthermore, cross-domain entry association retrieval is faced with practical challenges which include strong source heterogeneity, sparse connections among long-tail entries, and high noise existing in user behavior signals; All of these factors have influence upon the stability and interpretability which belong to ranking results.

Under this background, this article puts forward a retrieval method which is based on the Graphormer-Lite graph structure encoding model, and concentrates on the task of cross-domain knowledge item association retrieval in university digital libraries. This research arranges books, journal papers, graduate dissertations, class materials, writers, topic words, and subject departments into one united different-kinded graph. Through the usage of relation kind coding, structure distance calculation, and lightweight Graph Transformer expression study, the model promotes its capability of catching cross-domain connection signals, hence balancing online arrangement effectiveness and search quality. The core question which this paper plans to solve is the way to realize higher-quality, more explainable, and more engineering-practicable related retrieval under a digital library circumstance which is featured by the coexistence of complicated knowledge objects, various relation types, and restricted service time delay.

2 Methods

2.1 Cross-domain Knowledge Entry Graph Construction for University Digital Libraries

To support cross-domain knowledge entry association retrieval in university digital libraries, this paper first performs a unified graph-based modeling of the collection objects.Considering that university digital resources are characterized by dispersed sources, heterogeneous objects, and diverse relationships, this study takes books, journal articles, theses, and course resources as core knowledge entry nodes. It introduces subject headings, authors, schools/disciplines, database sources, and keyword entities as auxiliary nodes, mapping resources from different sources and with varying organizational granularities into a single graph space, as shown in Figure 1.

Figure 1: Schematic Diagram of the Mechanism for Constructing a Heterogeneous Graph of Cross-Domain Knowledge Entities in University Digital Libraries

In Figure 1, the left part stands for the cross-domain resource starting point, the right part draws the clear relation model, the middle area forms the unified heterogeneous graph, and the bottom part shows the place where text features, metadata features and structural features are injected together. This kind of graph expression keeps the differences between resource objects, and at the same time, it gives a unified expression basis for the follow-up connection search work. The data which the present research uses include six disciplinary domains: computer science, medicine, materials science, education, economics, and agriculture. In all, 120,000 core knowledge entry nodes have been arranged, which form 2.15 million band-style relation edges, and 38,624 user click and download records have been collected as weak supervision signals. Inside the node categories, volumes, journal essays, dissertations, and class materials act as the main search targets; subject terms, authors, schools/departments, database sources, and keyword entities are utilized to make supplement for subject affiliation, responsible entities, organizational hierarchy, and source context. To enhance the graph structure's capacity to capture real-world business semantics, this study retains relationship types such as authored_by , belongs_to_subject, cites/is_cited_by, shares_keyword, course_related_to, same_topic_cluster, co_accessed/co_downloaded, and same_repository_source.Among these, author relationships and disciplinary affiliations primarily derive from bibliographic metadata; citation relationships are obtained by parsing references in journal articles and theses; co-occurrence and topic cluster relationships are formed through subject term mapping and semantic clustering; and co-access and co-download relationships are extracted from log statistics to supplement usage evidence beyond static collections [13, 14].

In Figure 1, the left section represents the starting point of cross-domain resources, the right section depicts the explicit relation model, the middle region constructs the unified heterogeneous graph, and the bottom section displays the location where text features, metadata features and structural features are jointly injected. This kind of graph expressing mode retains the differences among resource objects, and meanwhile, it provides a unified expressing foundation for the subsequent connection searching work. The data that this current research utilizes contain six disciplinary fields: computer science, medicine, materials science, education, economics, and agriculture. In total, 120,000 core knowledge entry nodes are arranged, which compose 2.15 million belt-shaped relation edges, and 38,624 user click and download records are collected as weak supervision signals. Inside the classification of nodes, book collections, journal articles, graduate theses, and course materials serve as the chief searching objects; subject terms, authors, schools/departments, database sources, and keyword entities are employed to carry out supplementation for subject affiliation, responsible entities, organizational levels, and source background [15].

2.2 Graphormer-Lite Encoding and Association Retrieval Model

After constructing the heterogeneous graph of cross-domain knowledge entries, this paper further designs the Graphormer-Lite encoding and association retrieval model to learn the association strength between query entries and candidate entries. The overall structure of the model is shown in Figure 2.

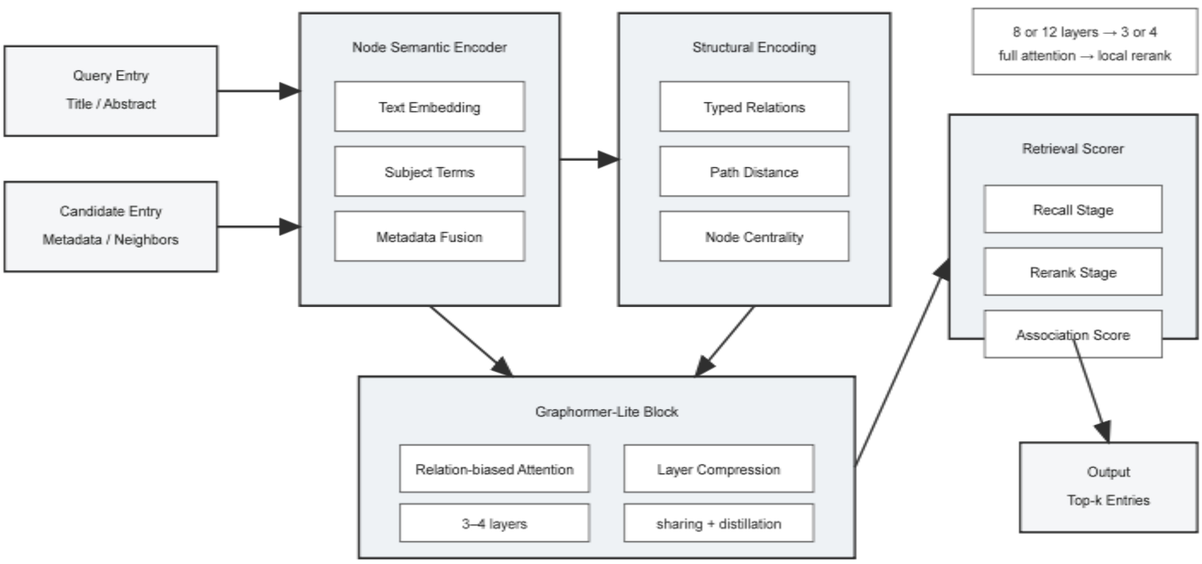

Figure 2: Schematic diagram of the Graphormer-Lite encoding and association retrieval mechanism.

In Figure 2, the left side inputs are constituted by the query item and candidate items; the center part in order includes the node meaning coder, structure coder, and the Graphormer-Lite core module; and on the right-hand side, there exists a two-step association grade calculation procedure and the output of Top-k. This architecture keeps Graphormer's capability to express relation and route information, meanwhile it presses deep global attention into a light framework which is fit for on-line search situations in digital libraries [16].

The node semantic encoder integrates titles, abstracts, subject headings, and metadata. Titles and abstracts are converted into semantic vectors via a text encoder, while subject headings, classification codes, publication years, source repositories, and resource types are fused with the text vectors after embedding mapping to form the initial node representation. The initial node representation is shown in Equation (1).

$$h_i^{(0)}=LayerNorm(W_t e_i^{txt}+W_m e_i^{meta}+b) \tag{1}$$

where e_i^{txt} represents the text vector, e_i^{meta} represents the metadata vector, and $h_i^{(0)}$ is the initial node representation. To mitigate biases caused by missing fields, the model employs learnable weights for text and metadata items, enabling books, journal articles, and course resources to obtain comparable representations within a unified space [17, 18].

To enhance the model's ability to distinguish heterogeneous relationships, this paper introduces structural biases in addition to semantic representations, incorporating relationship types, path distances, and node connection strengths into the encoding process. The corresponding bias terms are shown in Equation (2).

$$b_{ij} = a_r(r_{ij}) + a_d(d_{ij}) + \lambda \log(1 + deg_i) + \lambda \log(1 + deg_j) \tag{2}$$

where: r_{ij} denotes the relationship type between a pair of nodes; d_{ij} denotes the shortest path distance; $a_r(\cdot)$ denotes the relationship type mapping function; $a_d(\cdot)$ denotes the path distance mapping function; deg_i and deg_j denote node degree values; λ denotes the scaling coefficient; and b_{ij} denotes the structural bias. This term is directly incorporated into the attention score calculation, ensuring that different relationships make distinguishable contributions during the encoding phase.

In the backbone encoding stage, this paper does not adopt the standard Graphormer's 8-layer or 12-layer global attention structure, but instead compresses the encoding layers to 4 layers and performs relationship-biased attention calculations on the candidate set. The attention form is shown in Equation (3).

$$\alpha_{ij}^{(l)}=\frac{\exp\left(\frac{\left(\mathbf{W}_Q^{(l)}\mathbf{h}_i^{(l)}\right)^\top\left(\mathbf{W}_K^{(l)}\mathbf{h}_j^{(l)}\right)}{\sqrt{d}}+b_{ij}\right)}{\sum_{m\in N_k(i)}\exp\left(\frac{\left(\mathbf{W}_Q^{(l)}\mathbf{h}_i^{(l)}\right)^\top\left(\mathbf{W}_K^{(l)}\mathbf{h}_m^{(l)}\right)}{\sqrt{d}}+b_{im}\right)} \tag{3}$$

where: $\mathbf{W}_Q^{(l)}$ and $\mathbf{W}_K^{(l)}$ are the query and key matrices of layer l, respectively; d is the hidden dimension; $N_k(i)$ is the recalled local candidate set; and $\alpha_{ij}^{(l)}$ is the attention weight. The differences in their lightweight designs are shown in Table 1.

Table 1: Structural Comparison Between Graphormer-Lite and Standard Graphormer

Module	Standard Graphormer	Graphormer-Lite
Number of Encoding Layers	8 or 12 layers	3 or 4 layers
Attention Scope	Full graph or large-scale global attention	Local candidate set + relation-biased attention
Relationship Modeling	Relational bias, path encoding	Retaining relational bias and path encoding
Parameter Organization	Independent parameters across layers	Partial parameter sharing
Compression Methods	No dedicated compression	Teacher-student distillation
Candidate Processing	Tends toward large-scale unified encoding	Recall first, then refine
Inference Overhead	High	Significantly reduced
Scenario Adaptability	More user-friendly for offline analysis	More suitable for online relevant retrieval

In Table 1, the decrease of model complexity mainly comes from layer cutting, partial candidate attention, and teacher-pupil knowledge distillation.

Finally, the related retrieval scorer outputs a matching score between the query item and the candidate items, and employs joint training with both contrastive and ranking constraints, as shown in Equation (4).

$$s(q,c)=\mathrm{MLP}\left(\left[\mathbf{z}_q \| \mathbf{z}_c \| \left|\mathbf{z}_q-\mathbf{z}_c\right| \| \mathbf{z}_q \odot \mathbf{z}_c\right]\right) \tag{4}$$

$$\mathrm{L}=\mathrm{L}_{\mathrm{InfoNCE}}+\beta \mathrm{L}_{\mathrm{pair}} \tag{5}$$

where: $\mathbf{z}_q$ and $\mathbf{z}_c$ denote the query item representation and candidate item representation, respectively; $s(q,c)$ is the association score; $\mathrm{L}_{\mathrm{InfoNCE}}$ is the contrastive loss; $\mathrm{L}_{\mathrm{pair}}$ is the pairwise ranking loss; and β is the weight coefficient. This design preserves both semantic proximity and relational reachability during the candidate refinement stage, thereby enhancing the stability and discriminative power of cross-domain knowledge item association retrieval [19, 20].

2.3 Experimental Design and Evaluation Protocol

To verify the effectiveness of Graphormer-Lite in cross-domain knowledge item association retrieval in university digital libraries, this thesis sets up an experimental scheme which includes four aspects: data division, baseline configuration, evaluation indicators, and additional experiments. The experiment data set is obtained from the above-mentioned different kind graphs in six subject areas, which includes 120,000 core knowledge entry nodes, about 2.15 million band shape relation edges, and 38,624 click and download records. Log records and graph relations together were used for sample building: if there existed proof of stable course connections, appearing together in topic groups, or high-frequency co-browsing between two entries, they were divided as positive samples; when entries have likeness in subject words or origin storage banks but have no behavior support, therefore they are built as samples which are hard to be classified. The experiment arrange is displayed in Table 2.

Table 2: Graphormer-Lite Experimental Design and Evaluation Protocol.

Item	Setting
Subject Domain	Computer Science, Medicine, Materials Science, Education, Economics, Agriculture
Graph Size	120,000 nodes; 2.15 million edges
Log Signals	38,624 click/download records
Data Split	Training: 70%; Validation: 10%; Testing: 20%
Candidate Strategies	Initial screening: 100; Final selection: 20
Baseline	BM25, Sentence-BERT, LightGCN, HAN, HGT, Graphormer
Model in this Paper	4 layers; 256-dimensional; 4-head attention
Optimization Settings	AdamW; (2×10^(−4)); batch size 32; 30 epochs
Quality Metrics	Recall@10, Recall@20, nDCG@10, MRR, MAP
Efficiency Metrics	Latency, GPU memory, model size
Supplementary Experiments	Ablation, Long-tail, Interdisciplinary Robustness

In Table 2, the data partitioning, candidate set size, and evaluation metrics are all designed around the actual retrieval workflow of digital libraries, which follows a "recall-first, then ranking" approach.

The data have been divided by query entries into training set, validation set and test set, the ratio of which is 7:1:2, and a consistent distribution among six subject domains is kept by this division method. In the training stage, a sparse recall method is at first utilized to get 100 candidate items, hence after that the first 20 candidates are input into the Graphormer-Lite ranking module. This kind of design can hold enough structural difference space, meanwhile it lets calculation cost be controlled; the basic method is in accordance with candidate restriction tactics in study of document-knowledge graph-strengthened searching and knowledge graph-expanded searching [21, 22].

The baseline models have four kinds of classifications: BM25 stands for the traditional text search, Sentence-BERT stands for dense semantic search, LightGCN, HAN, and HGT stand for representative graph structure type search, and the standard Graphormer acts as the high-load graph Transformer baseline model. The model that this paper uses is set up to have 4 encoding blocks, one hidden dimension of 256, 4-head attention, and one local candidate size of 20. The optimizing tool is utilized to employ AdamW, with a learning rate of 2×10^{-4}, a batch size that is 32, and a maximum number of 30 training epochs.

Evaluation metrics consider both retrieval quality and deployment efficiency.Quality metrics include Recall@10, Recall@20, nDCG@10, MRR, and MAP; efficiency metrics include average inference latency, GPU memory usage, and parameter size. In addition to the main experiments, we conduct ablation studies, long-tail item tests, and cross-domain robustness analysis to identify the specific impacts of relationship bias, path encoding, and distillation compression on performance [23, 24].

3 Results and Discussion

3.1 Overall Retrieval Performance Comparison

In overall performance comparisons, presenting a single set of primary metrics is often insufficient to determine whether a model is truly suitable for the university digital library scenario. This is because cross-domain knowledge item retrieval involves more than simply distinguishing between "relevant" and "irrelevant" results; it also involves organizational differences across disciplinary domains, the difficulty of matching different resource types, and the actual contribution of various relational cues in the top rankings.Therefore, this section presents the analysis in the order of "overall results—scenario-specific results—relationship-supported results."First, we use primary retrieval metrics to observe the overall advantages of Graphormer-Lite relative to traditional text retrieval, general graph models, and standard Graphormer; subsequently, we break down the results at the disciplinary domain and cross-resource type levels to determine whether these advantages are stable; finally, by combining the distribution of relational contributions in the Top-k hits, we illustrate which structural evidence collectively underpins the improvement in ranking quality. The overall retrieval results are shown in Figure 3.

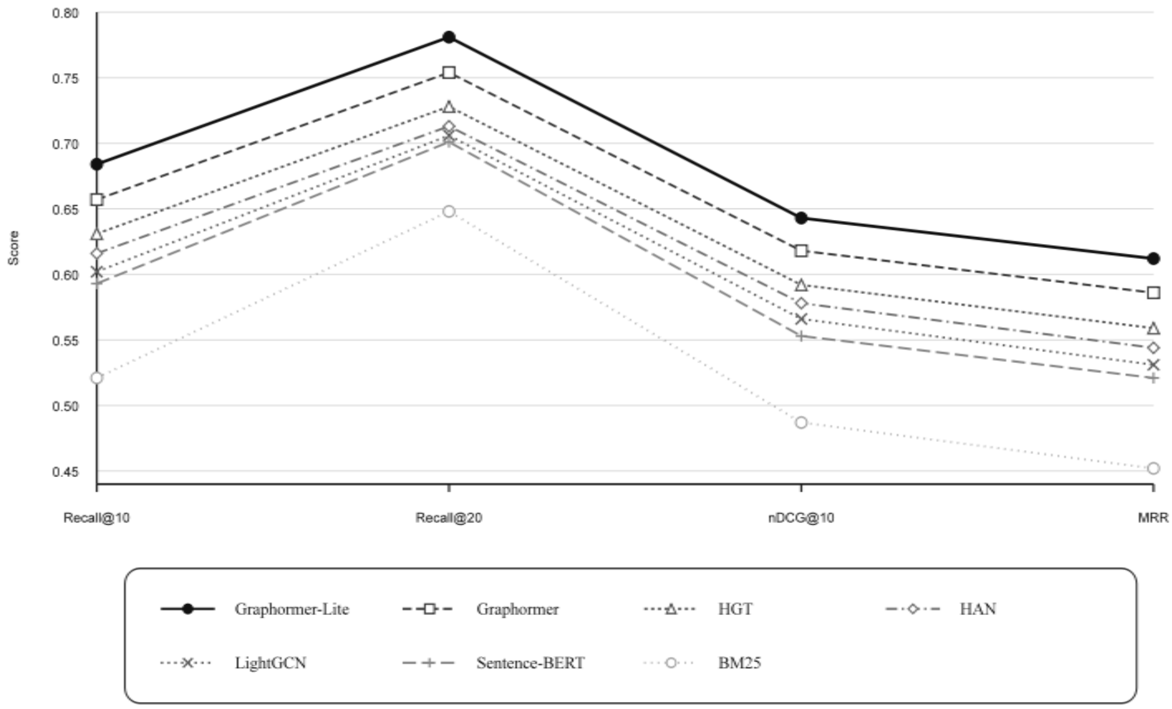

Figure 3: Comprehensive comparison of different models on primary retrieval metrics

In Figure 3, Graphormer-Lite achieves the highest values across all four metrics—Recall@10, Recall@20, nDCG@10, and MRR—with scores of 0.684, 0.781, 0.643, and 0.612, respectively; the corresponding results for the standard Graphormer are 0.657, 0.754,0.618, and 0.586, respectively; HGT achieved 0.631, 0.728, 0.592, and 0.559; Sentence-BERT achieved 0.593, 0.701, 0.553, and 0.521; and BM25 performed the worst.Compared to the standard Graphormer, Graphormer-Lite achieved improvements of 4.11% and 4.05% in Recall@10 and nDCG@10, respectively, indicating that the lightweight processing did not weaken structural discrimination capabilities but rather improved the quality of top-ranking results.These results indicate that, in the context of cross-domain association retrieval in university digital libraries, relying solely on text similarity makes it difficult to consistently identify high-quality associated entries; incorporating both relational semantics and local topology into the ranking process is more effective.

The distribution of results across different disciplinary domains and resource types is shown in Figure 4.

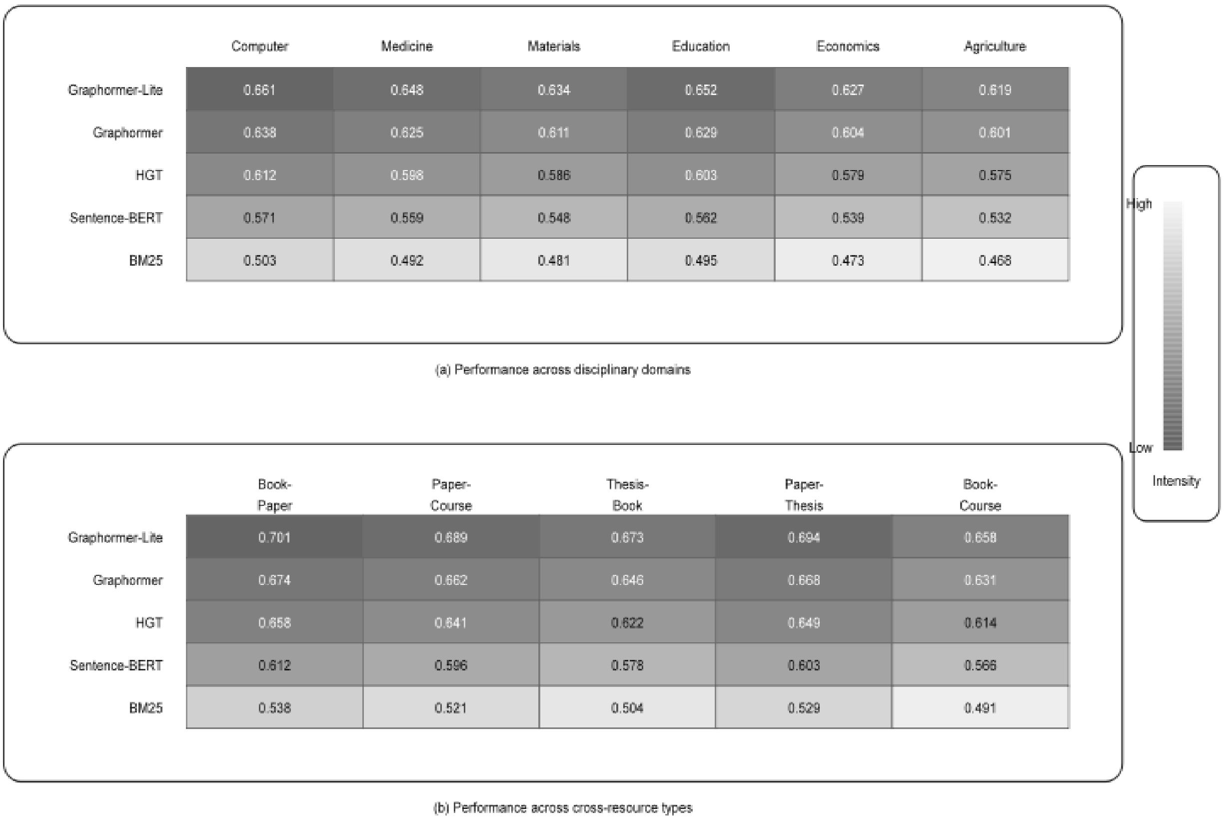

Figure 4: Collage of related search performance across different disciplinary domains and resource types.

From Figure 4(a) we can see, Graphormer-Lite keeps the first place in six different discipline fields—computer science, medicine, materials science, education, economics, agriculture—and its nDCG@10 numerical values are 0.661, 0.648, 0.634, 0.652, 0.627, 0.619, separately. The entirety of changes in range are very small, hence this indicates that the model has good adaptation toward differing gathering structures. Figure 4(b) further makes clear that the model obtains more obvious promotions in conventional cross-domain matching works such as book-article, article-course resource, and thesis-book, with Recall@10 arriving at 0.701, 0.689, and 0.673, respectively—these represent growths of 6.8%, 7.4%, and 8.1% compared with HGT. This shows that Graphormer-Lite has higher sensitivity toward "content-connected but source-different" item pairs, hence can effectively make up for the deficiencies of pure semantic matching.

The distribution of relationship contributions among the *top-k* correct hits is shown in Figure 5.

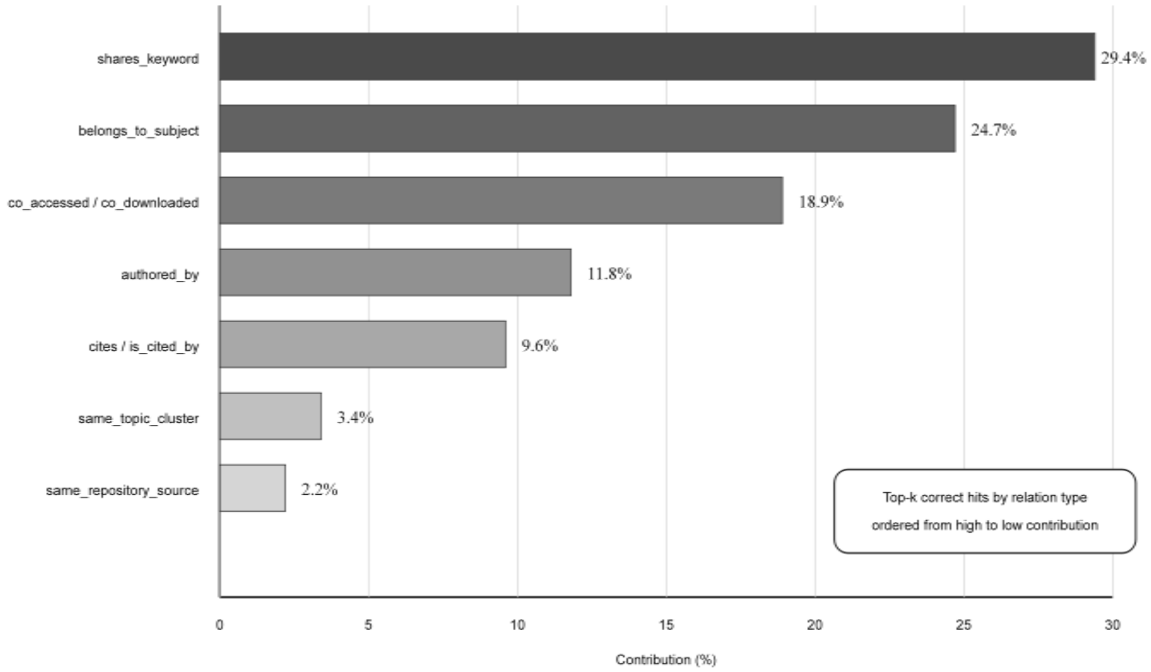

Figure 5: Distribution of relationship types in the Top-K hits.

In Figure 5, shares_keyword, belongs_to_subject, and co_accessed/co_downloaded are three main supporting relationships, therefore they account for 29.4%, 24.7%, and 18.9% of total, respectively; authored_by and cites/is_cited_by respectively occupy 11.8% and 9.6% in the proportion. This distribution shows that the high-quality matching results for cross-domain knowledge points depend more on the combined action of co-occurring topics, subject attribution and user behavior signals, instead of being pushed by a single strong connection. This tendency is in accordance with the conclusion that many relationships together work to decide rank quality in knowledge graph-raised retrieval [25].

A comprehensive analysis of Figures 3 through 5 reveals that the advantages of Graphormer-Lite are reflected not only in the improvement of overall metrics but also in its stable performance across multidisciplinary and multi-type resource matching tasks.

3.2 Ablation and Efficiency Analysis

After we have confirmed that the whole model obtains effective retrieval results, therefore two more questions need to get responses: first, which modules have contribution to the promotion of Graphormer-Lite's performance; and secondly, whether these obtained benefits are realized at an allowable calculation expense. To the digital libraries of universities, these two questions have the same importance. If promotion of model cannot be clearly assigned to relation building or structure coding, the method meaning of this model is hard to explain; On the opposite side, if this model obtains high accuracy but must pay the price of obvious time delay and parameter scale, its feasibility for on-line arrangement and use is greatly lowered. The outcome of the key module cutting experiment are displayed in Figure 6.

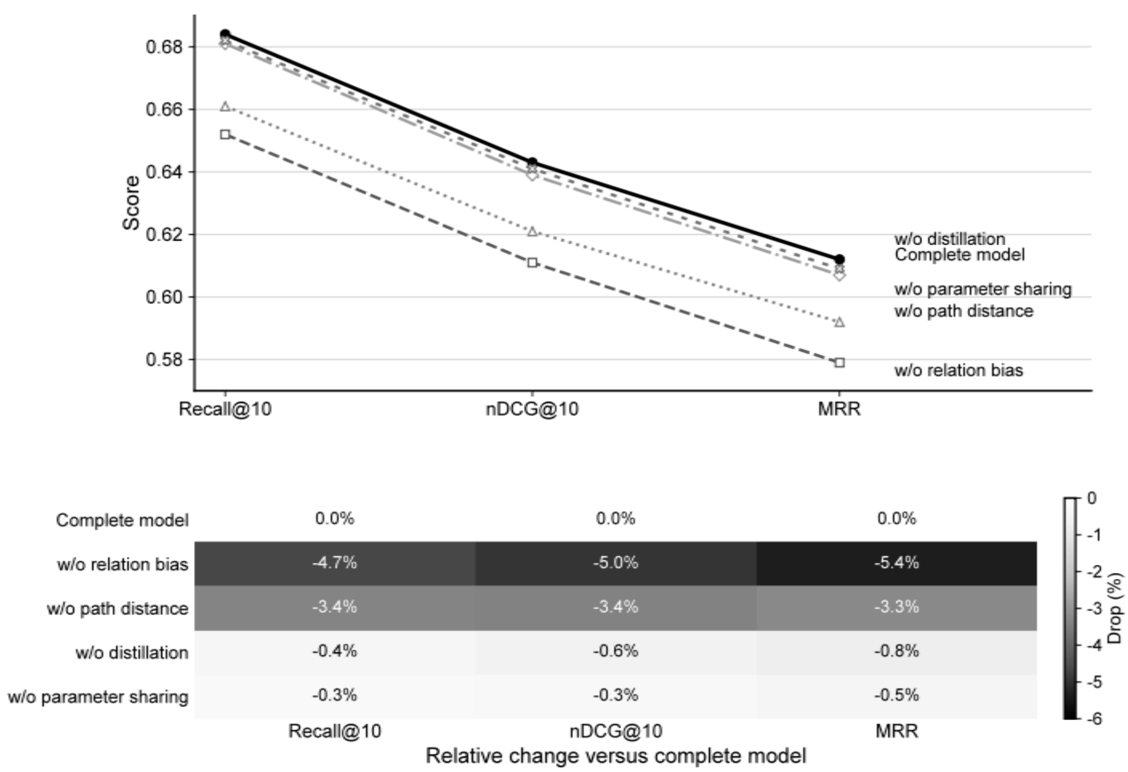

Figure 6: Comparison of Graphormer-Lite key module ablation results.

In Figure 6, the upper part gives a direct contrast of the complete model and each ablation model with regard to Recall@10 and nDCG@10, hence the lower part further explains the size of performance drop in terms of relative percentage reduction. The entire model obtains Recall@10 and nDCG@10 numerical values of 0.684 and 0.643, respectively. After we have removed the relationship type bias, two metrics have fallen to 0.652 and 0.611, which represent decreases of 4.68% and 4.98% respectively, hence this is the most significant decline in all ablation settings. After we have removed the path distance encoding, the two metrics have dropped to 0.661 and 0.621, with decreases of 3.36% and 3.42%, respectively. On the opposite side, taking away the distillation restrictions and parameter sharing brought about only a small decrease in the main metric, hence this shows that these parts mainly work to make the model smaller and guarantee the stability of training, therefore the structural distinguishing ability which is formed together by relationship deviation and path distance is still the real base which supports the cross-domain connection identification. From the aspect of method principle, this outcome conforms to the multi-relation coordination which is reflected in the above Figure 5. The balance which must be traded off among accuracy, delay, and parameter size is displayed in Figure 7.

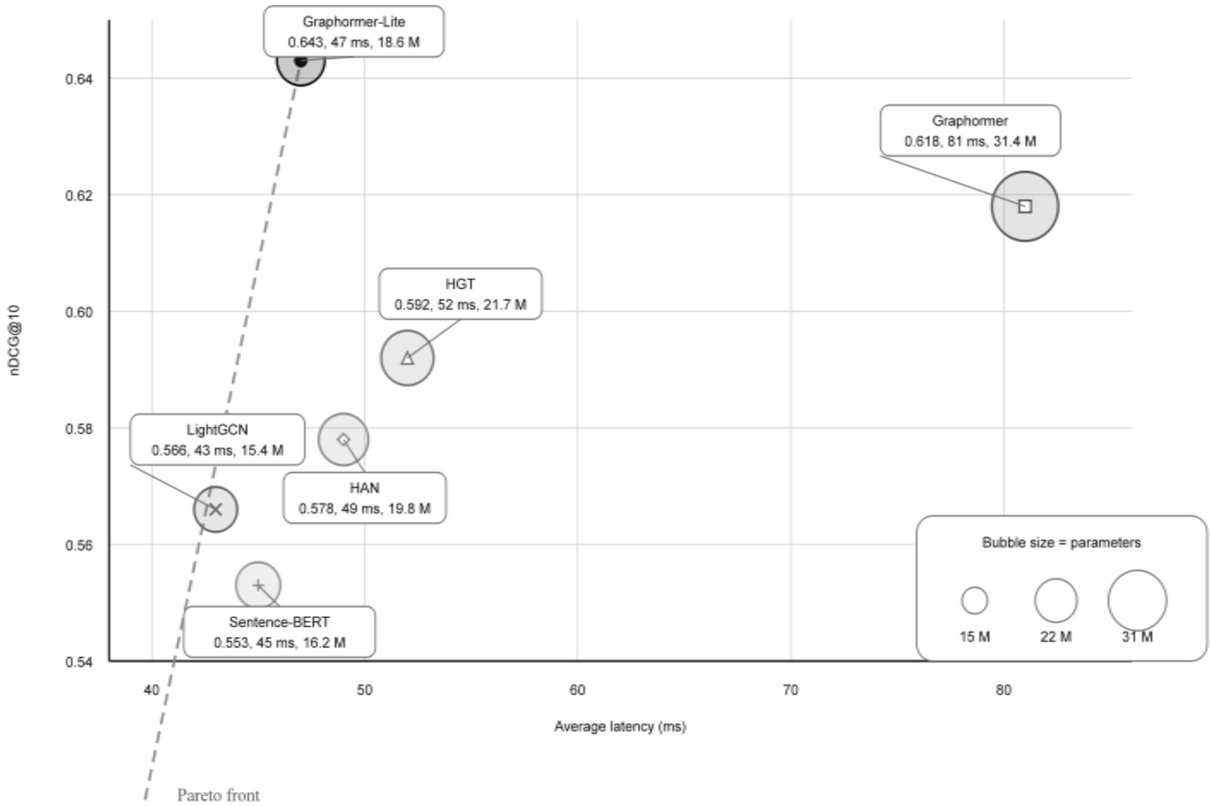

Figure 7: Model Accuracy-Latency-Parameter Scale Trade-off Plot.

In Figure 7, the horizontal axis stands for average inference time delay, the vertical axis stands for nDCG@10, and the dimension of the bubbles shows the parameter size. Graphormer-Lite is situated in a good trade-off area, having an nDCG@10 of 0.643, an average inference delay time of 47 ms, and a parameter size of 18.6 M; The standard Graphormer can reach an nDCG@10 of 0.618, a time delay of 81 ms, and a parameter quantity of 31.4 M. When compared with the standard Graphormer, the Graphormer-Lite can cut down inference waiting time by 41.98% and the quantity of parameters by 40.76%, and at the same time it still keeps higher ranking quality. HGT, HAN, and LightGCN have lower time delay but much lower precision rate; although BM25 can give the most quick reply speed, it therefore gives out the lowest level of ranking effect. This proves that the superiority of Graphormer-Lite does not only lie in the enhanced accuracy, but also lies in its capability of holding performance increments within computable costs that can be deployed, hence this is especially pragmatic for university digital library search systems which have the demand for real-time responses. The distribution that results of long-tail and cold-start entries is displayed by Figure 8.

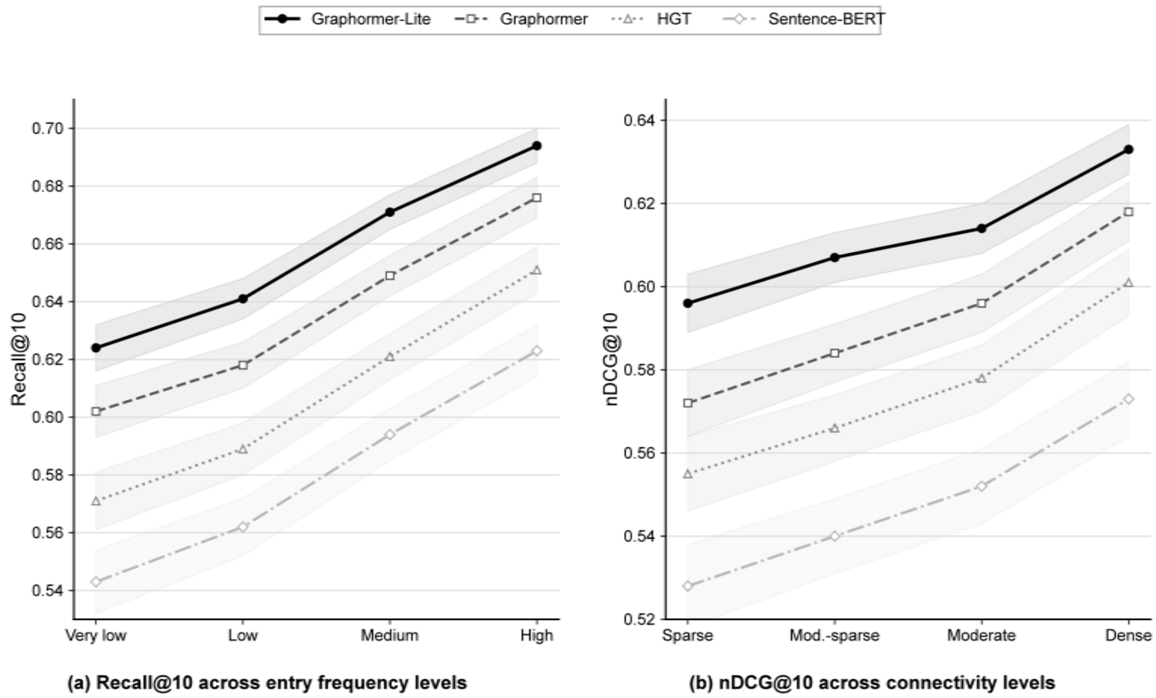

Figure 8: Performance comparison of long-tail and cold-start items.

Figure 8(a) shows that on the low-frequency item subset, Graphormer-Lite's Recall@10 is 0.641, higher than Graphormer's 0.618 and HGT's 0.589; as item frequency increases, the performance of all models improves, but Graphormer-Lite maintains its lead in the medium- and high-frequency ranges.Figure 8(b) shows that on the cold-start subset with the highest connection sparsity, Graphormer-Lite achieves an nDCG@10 of 0.596, outperforming Graphormer's 0.572 and HGT's 0.555; as connection density gradually increases, this model's advantage persists in the medium- and high-density ranges.This indicates that even when entries lack sufficient interaction records or stable adjacency relationships, Graphormer-Lite can still maintain relatively stable ranking capabilities by relying on local structural biases.

Through overall comprehensively analysis of the Figures 6 to 8 we can discover that the Graphormer-Lite's promotion of performance has the clear origins, it mainly depends on relationship type bias and path distance encoding; its engineering good points are also very clear, which are shown in smaller time delay and a more tight parameter scale; Under the long-tail and cold-start situations, the model also has not appeared obvious unstable performance.

3.3 Case Study, Error Analysis, and Deployment Implications

This section introduces two supplementary perspectives: case studies and error analysis. The former demonstrates how the model generates cross-domain relevance results in specific tasks, while the latter identifies key factors limiting the model's upper performance bounds. Building on this foundation, we discuss its deployment for fine-tuning in university digital library retrieval systems and directions for future optimization. A typical cross-domain relevance retrieval case is shown in Figure 9.

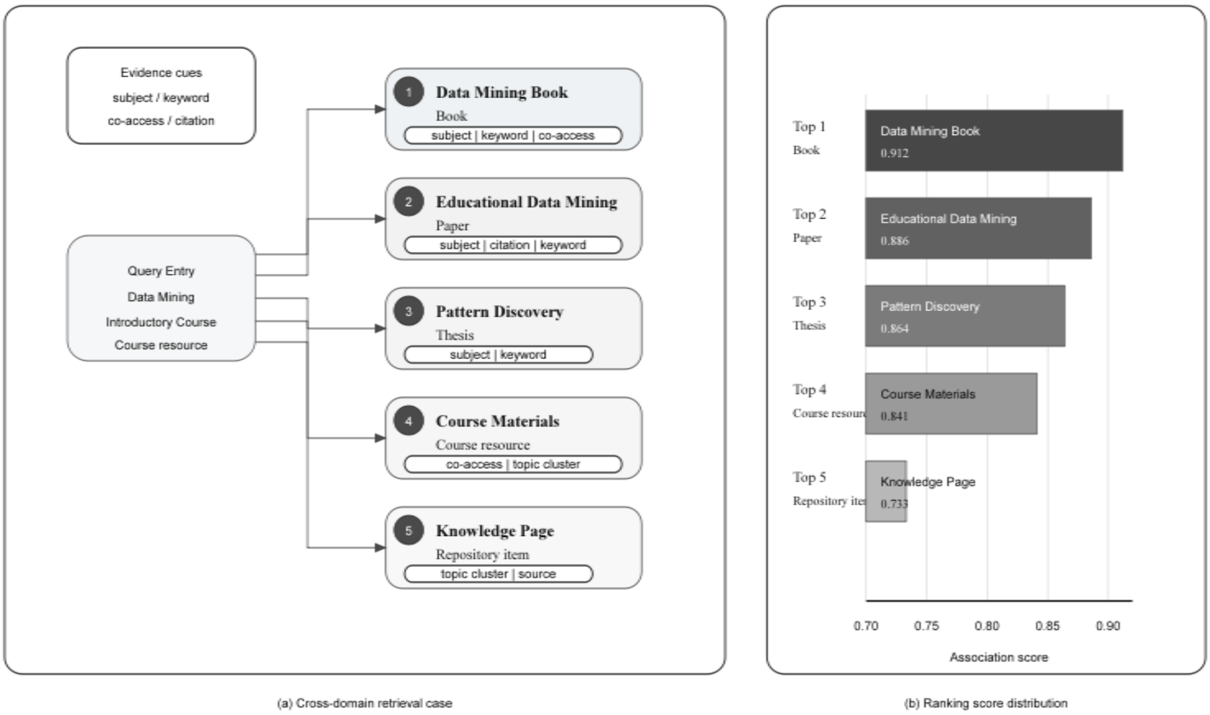

Figure 9: A typical cross-domain association retrieval case and the distribution of ranking scores.

In Figure 9(a), when the course resource which corresponds to "Data Mining Introductory Course" is taken as the query item, the five top results which Graphormer-Lite gives back are, in order: teaching books, review papers, master degree theses, extra course materials, and database knowledge web pages. These five result categories cover books, articles, theses, course resources, and specialized entries within the database, demonstrating that the model can organize knowledge objects of different origins and granularities within the same retrieval chain.In Figure 9(a), the top four results all share either a common subject affiliation, shared keywords, or evidence of concurrent access, thereby forming relatively stable local connections with the query item; the final database knowledge page retains only weak connections at the subject cluster and source levels, resulting in a relatively lower association strength. Figure 9(b) further illustrates the distribution of ranking scores for the top five results.It can be seen that the association scores for Top 1 to Top 4 are 0.912, 0.886, 0.864, and 0.841, respectively, remaining within a high range overall, indicating that these four types of results are relatively close to the query entry in terms of both semantic content and structural evidence;The score for Top 5 drops to 0.733, creating a noticeable gap between it and the top four results. This distribution aligns with the relationship patterns observed in Figure 9(a): when evidence such as subject, keyword, and co-access occurs together, results are more likely to consistently rank highly; when entries retain only weak connections at the topic cluster or source level, the ranking scores drop significantly.This demonstrates that the strength of Graphormer-Lite lies not only in retrieving relevant entries but also in its ability to rank cross-domain results in a relatively hierarchical manner. The distribution of error sources is shown in Figure 10.

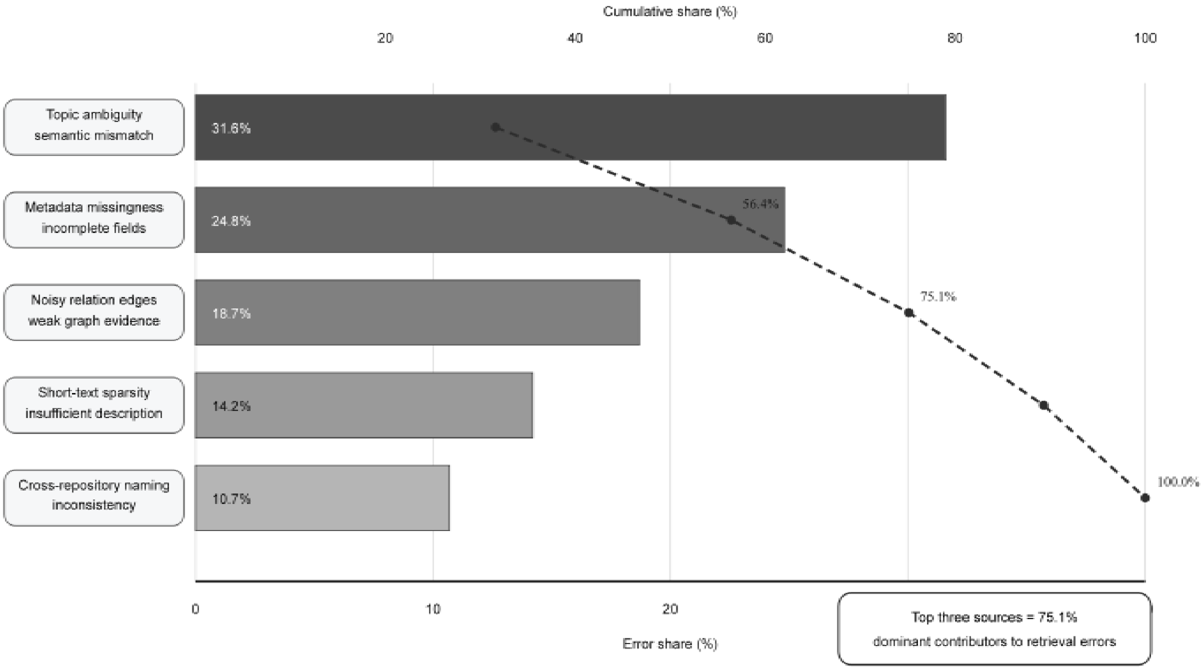

Figure 10: Distribution of error sources in related search.

In Figure 10, it is topic ambiguity, missing metadata and relationship edge noise that are the three main error sources, which account for 31.6%, 24.8% and 18.7% respectively, and the sum is 75.1%; the lack of enough short-text information and the non-uniform naming across different databases hold the shares of 14.2 percent and 10.7 percent accordingly. These findings show that the present mistakes are mainly gathered on two aspects: not enough semantic distinguishing ability and not unified cataloguing quality. Concretely speaking, the ambiguity of subject frequently appears among homonymous words, subject terms with wide meanings, or terminology that is shared among cross disciplines; lacking metadata mainly shows itself as unfinished abstracts, key words, or classification numbers; and the noise on relationship edges normally originates from low-quality shared access records or wrong automatic mapping across different databases. The distribution which Figure 10 shows tells us that although the model's structure can promote the quality of association ranking, the problems of incompleteness and inconsistency on the data side still directly restrict the final results.

From the view of deployment, the case structure that is shown in Figure 9 and the error sources that are found in Figure 10 together show that Graphormer-Lite is more suitable to act as a fine-tuning module in the retrieval chain of a digital library. A cautious deployment method is as below: the front end at first carries out an initial check by using BM25 or dense search, after that Graphormer-Lite carries out structured reordering of the top 20 candidate items, meanwhile outputs explainable clues for example common subject words, discipline belongings, or co-access connections. This method not merely controls the costs of online responses, but also assists in promoting the understandability of the showing of results.

4 Conclusion

This thesis discusses the problem of cross-domain knowledge item connection search in university digital libraries, carries out an overall research that covers heterogeneous graph arrangement, lightweight relation coding to the verification of search effect. The outcomes show that uniting the modeling of resource content, structural connections, and use behavior can effectively enhance the shortcomings of traditional retrieval, such as faint cross-domain links and lacking ranking level. To speak specifically, the results of research can be concluded in the way below:

(1) The present article builds one heterogeneous graph expression frame that includes things like books, journal papers, degree theses, teaching course materials, topic words, writers, universities/academic fields, and database origins. This framework makes it possible that textual content, cataloging attributes, structural relationships and behavioral cues are expressed collaboratively within one single graph space, thus it provides a unified data foundation for associative retrieval across different resource types.

(2) This present article puts forward the Graphormer-Lite light-weight model for relationship encoding. While it still keeps the capacity of expressing relation kinds, path lengths and part structure, it cuts calculation cost through layer compression, candidate limits, and parameter sharing and distillation methods. Experimental outcome tell us that this model can display a steady ascendancy in all main index for searching, cross-resource-type works, and long-tail and cold-start situations, hence it obtains a comparatively better balance between accuracy and running speed.

(3) The method that we put forward still is constrained by the quality of graph data, the completeness of metadata, and the strength of log supervision. When carrying out cross-institution transfer, this work can also be restricted by divergences in cataloging norms and differences in the organizing of resources. In the future, research work should place emphasis on incremented graph renewing, weak-noise relation cleansing, cross-library verification, and explainable feedback for outcomes, hence further promoting the model's transfer ability and long-time working stability.

About the Author

Hui Liu was born in Linyi, Shandong, P.R. China, in 1982. She received her master's degree from Qufu Normal University, P.R. China. She is currently employed at the Library of Jining Medical University. Her primary research areas include library culture development and cultural services, information resource management, and reader services.

References

[1] Albarede, L., Mulhem, P., Goeuriot, L., et al. (2023). Heterogeneous graph attention networks for passage retrieval. Information Retrieval Journal, 26, Article 11.

[2] Wang, Y., Liu, J., Xu, X., et al. (2023). Efficient and effective academic expert finding on heterogeneous graphs through (k, P)-core based embedding. ACM Transactions on Knowledge Discovery from Data, 17(6), Article 85, 1-35.

[3] Huang, Z., Tang, D., Zhao, R., et al. (2024). A scientific paper recommendation method using the time decay heterogeneous graph. Scientometrics, 129(3), 1589-1613.

[4] Shi, K., Liu, K., & He, X. (2024). Heterogeneous hypergraph learning for literature retrieval based on citation intents. Scientometrics, 129(7), 4167-4188.

[5] Kasela, P., Pasi, G., & Perego, R. (2025). PARK: Personalized academic retrieval with knowledge graphs. Information Systems, 134, 102574.

[6] Bi, R. (2025). An adaptive semantic retrieval framework for digital libraries integrating graph neural networks, ontology, and user behavior. Scientific Reports, 15, Article 40528.

[7] Wu, Y., Pan, X., Li, J., et al. (2024). Interpretable answer retrieval based on heterogeneous network embedding. Pattern Recognition Letters, 182, 9-16.

[8] Dessí, D., Osborne, F., Buscaldi, D., et al. (2025). CS-KG 2.0: A large-scale knowledge graph of computer science. Scientific Data, 12, Article 964.

[9] Xu, J., Yu, C., Xu, J., et al. (2025). PubMed knowledge graph 2.0: Connecting papers, patents, and clinical trials in biomedical science. Scientific Data, 12(1), 1018.

[10] Cai, Z., Xu, N., Cai, L., et al. (2025). Educational knowledge graph-based intelligent question answering for automatic control disciplines. Applied Intelligence, 55(13), Article 943.

[11] Zhao, X., Wang, G., & Lu, Y. (2025). MDKAG: Retrieval-augmented educational QA powered by a multimodal disciplinary knowledge graph. Applied Sciences, 15(16), 9095.

[12] Gao, F., Xu, S., Hao, W., et al. (2025). KA-RAG: Integrating knowledge graphs and agentic retrieval-augmented generation for an intelligent educational question-answering model. Applied Sciences, 15(23), 12547.

[13] Wang, T., Pan, Z., Hu, G., et al. (2023). Self-supervised heterogeneous graph learning with iterative similarity distillation. Knowledge-Based Systems, 276, 110779.

[14] Chang, Y., Zhou, W., Cai, H., et al. (2023). Meta-relation-assisted knowledge-aware coupled graph neural network for recommendation. Information Processing & Management, 60(3), 103353.

[15] Bi, Z., Cheng, S., Chen, J., et al. (2024). Relphormer: Relational graph transformer for knowledge graph representations. Neurocomputing, 566, 127044.

[16] Shi, F., Li, D., Wang, X., et al. (2025). TGformer: A graph transformer framework for knowledge graph embedding. IEEE Transactions on Knowledge and Data Engineering, 37(1), 526-541.

[17] Tao, H., Zhang, Z., Jiang, B., et al. (2025). Learning efficient linear graph transformer via graph-attention distillation. Machine Intelligence Research, 22(6), 1138-1152.

[18] Huang, C., Yu, F., Wan, Z., et al. (2024). Knowledge graph confidence-aware embedding for recommendation. Neural Networks, 180, 106601.

[19] Zhang, H., Wang, L., Sun, Z., et al. (2024). Knowledge-aware dual-channel graph neural networks for denoising recommendation. The Computer Journal, 67(5), 1607-1618.

[20] Wang, Y., Xie, Q., Tang, M., et al. (2025). Knowledge memory graph convolution network for cross-domain recommendation. Knowledge-Based Systems, 317, 113415.

[21] Knollmeyer, S., Akmal, M. U., Koval, L., et al. (2024). Document knowledge graph to enhance question answering with retrieval augmented generation. In 2024 IEEE 29th

International Conference on Emerging Technologies and Factory Automation (ETFA) (1-4).

[22] Linders, J., & Tomczak, J. M. (2025). Knowledge graph-extended retrieval augmented generation for question answering. Applied Intelligence, 55(17), Article 1102.

[23] Zhu, X., Xie, Y., Liu, Y., et al. (2025). Knowledge graph-guided retrieval augmented generation. In Proceedings of NAACL 2025 (Long Papers) (pp. 8912-8924).

[24] Hu, Y., Lei, Z., Zhang, Z., et al. (2025). GRAG: Graph retrieval-augmented generation. In Findings of the Association for Computational Linguistics: NAACL 2025 (4145-4157).

[25] Wang, S., Fan, W., Feng, Y., et al. (2025). Knowledge graph retrieval-augmented generation for LLM-based recommendation. In Proceedings of ACL 2025 (Long Papers) (pp. 27152-27168).